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Brain Interface to Control a Tele-Operated Robot

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Abstract. An electroencephalography (EEG) based brain computer interface (BCI) system with the ability of choosing among 4 options reliably every 1 second has been developed. The system has been used to control a tele-operated robot or wheelchair. The commands from the BCI system have been used as high and low level commands to control the tele-operated robot/wheelchair. High level BCI commands take advantage of autonomous navigation implemented on the target device for indoor and outdoor environments. The BCI system has been running at Northeastern University while the robot/wheelchair were at Worcester Polytechnic Institute (WPI).

Keywords: SSVEP, BCI, Robot, Wheelchair, Autonomous Navigation, Probabilistic Filtering

1. Introduction

EEG-based brain-computer interfaces (BCIs) can be categorized into three categories, steady state visually evoked potentials (SSVEP) [Sutter, 1992; Nezamfar et al., 2011], event-related potentials (ERP) [Krusienski et al., 2008], and motor imagery signals [Wolpaw, 2012]. Among these categories, SSVEP signals are the fastest and they have higher signal to noise ratio (SNR). Therefore, they are more suitable for control applications. One of the major target groups to use such systems are people who are functionally locked-in, or who have extremely little muscle movements. We developed a closed-loop brain-controlled tele-operated robot system that currently utilizes SSVEP-based command inference and interfaces with a variety of robots including Oryx 2.0, a planetary rover, a standard power wheelchair, and iCreate. The framework allows the operator to provide high and low level control commands to the robotic device, which might be tele-operated or could be providing a lift to the operator. The system can be extended by introducing more comprehensive assistive robots in the control loop and developing an improved inference assessment algorithm.

2. Brain-Computer Interface

The BCI in this work is an EEG-based system that utilizes SSVEP. Signals are generated by showing multiple flickering checkerboards on the screen, representing different command options. Each checkerboard inverts its colors according to a set of pseudo-random bit sequences called M-sequences. When the subject attends to one of the checkerboards to demonstrate the intention to select the corresponding command, a response signal corresponding to the one attended is generated in visual cortex. Consequently, by classifying this response according to the signature responses for each bit sequence, the system can decide on the command intended by the operator [Nezamfar et al., 2011].

2.1. BCI Operation

The EEG signal acquisition is done using a g.USBamp (g.tec). Only one electrode, placed on Oz according to the international 10/20 system, is used to sense and classify the brain activity. During calibration, which takes about 5 minutes, each M-sequence will be presented 50 times. Based on previous analysis [Nezamfar et al., 2011], template signals built using 50 repetitions of M-sequence periods are highly robust and result in high classification accuracy. After examining the calibration performance using 5-fold cross-validation, template signals $\mathbf{t}_i$ in response to each checkerboard's flickering pattern are generated. The distance between the operator's eye and the display was 60 cm and each checkerboard, containing 7×7 checkers, was 7 cm by 7 cm.

2.2. Classification Method

The classifier used is a matched filter classifier. To classify the EEG signal into one of the four choices, classifier extracts EEG signal $\mathbf{y}$ in response to a complete presentation of a sequence using a synchronization signal which marks the beginning of the presentation of the M-sequences along with the EEG signal. Next the correlation $\rho_i = \mathbf{y}^T \mathbf{t}_i$ between each template signal $\mathbf{t}_i$ and the extracted portion of EEG signal $\mathbf{y}$ is taken and the one with the highest correlation will be considered as the decision $D = \arg\max_i \rho_i$. M-sequences used are of length 31 bit, and the frequency of the presentation is 30 Hz, so a complete presentation of a sequence takes about 1.03 seconds. Therefore, the classifier

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is able to detect decisions roughly every one second. SSVEP responses by nature have about 100 ms delay, in other words the effect of the stimuli shows up in the EEG signals approximately 100 ms after the stimuli onset. The network delay between the BCI system and the robot was 140ms on average. Considering all of the above, the time period between subject making a decision and robot receiving the new command over the network is less than 1.3 s.

2.3. Probabilistic filtering of the human input

In this work, we have proposed and implemented a probabilistic context-aware filter which ensures a desired level of confidence in BCI-generated commands by incorporating the human/BCI probabilistic model with the probabilistic transition model calculated based on the context [Russel, 2010]. The two main components defining a probabilistic filter behavior are sensor model and transition model. The sensor model $P(X_{t+1}|E_{1:t+1})$ describes the probabilistic relationship between the human intended destination (or command) and the actual measured BCI output at time $t+1$ which can be dynamically updated based on the user input log available up to the current moment. Transition model $P(X_{t+1}|X_t)$, describes the probabilistic relationship between the current human intent and next human intent. With these definitions, the belief state can be calculated recursively $P(X_{t+1}|E_{1:t+1}) = \alpha P(E_{t+1}|X_{t+1}) \sum_{x_t} P(X_{t+1}|x_t) P(x_t|E_{1:t})$ where x_t is a particular value of the random variable X_t, and α is a normalizing constant that makes the belief state probabilities sum to 1. Each new BCI command updates the belief state of the user's intention. Now, we can generate a new destination setpoint for the path planner only if probability of one of the values in the belief state exceeds a predefined threshold, and is different from the previously set destination setpoint.

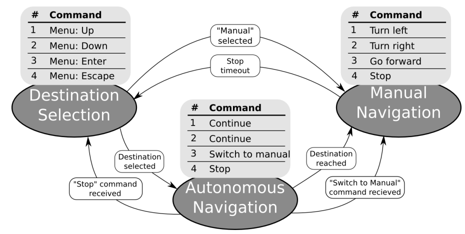

Figure 1: System State Diagram.

3. Results and Discussion

To verify the effect of high level commands with probabilistic context-aware filtering we defined three destinations D_1, D_2 and D_3 as the three high level choices. The subject was asked to move the wheelchair from $D_3 \overset{10m}{\to} D_2 \overset{6m}{\to} D_1 \overset{16m}{\to} D_3$ three times without probabilistic filtering and three times with probabilistic filtering. In total a 192 meter distance was covered in the evaluation. Table 1 shows the time needed to complete each route which verifies that this filtering can reduce the task duration. The target device needs to know the environment, which can be done once and updated each time a task is executed. In this experiment, the wheelchair tachometer, a 2D laser range finder (LIDAR), and an inertial measurement unit (IMU) constitute the perception of the robot. In the BCI system using pseudo-random bit sequences has numerous advantages over using frequencies to induce SSVEP response. Firstly, M-sequences are broadband sequences, therefore it is more robust to background activity in specific frequency bands. Secondly, it allows the usage of more stimulus objects e.g. checkerboards, than the frequency based presentation, because as the frequencies get closer with increasing number of stimuli, the separability of peaks in power spectrum considerably decreases.

Table 1: *Experiment Task Durations.*

Route	Duration W.O. Filter, [sec]				Duration W. Filter, [sec]			
	1	2	3	Avg.	1	2	3	Avg.
$D_3 \to D_2$	60	64	62	62.0	44	51	42	45.7
$D_2 \to D_1$	60	54	40	51.3	35	35	32	34.0
$D_1 \to D_3$	109	145	150	134.7	56	54	75	61.7

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